Spatial sampling effect of laboratory practices in a porphyry copper deposit

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ABSTRACT

Sampling protocols usually concern the way some kilograms of material are reduced to some grams with the same properties, but another protocol has to be considered: the choice of the samples to be used for estimating the resources of the deposit or some of its attributes.

An important attribute is the metallurgical recovery, calculated with data sampling the deposit, on which laboratory tests are made to reproduce the metallurgical recovery process at a reduced scale. Such tests are very few because they are expensive; hence, the idea to combine them with exploratory data where the sole in situ grade is known using geostatistical techniques.

While trying to put into practice this idea in a porphyry copper deposit located in the Chilean Central Andes, we encountered a surprising situation: laboratory tests and exploration measurements are supposed to use the same material but the total grades they measure do not have the same spatial variability.

The paper presents the study and the impact of four causes.

- Spatial restriction: laboratory samples do not cover the same domain as exploration data.
- Regularization: laboratory and exploration samples do not have the same size.
- Sampling density: in the rich unit of the studied area, there are about two hundred laboratory samples and four thousand exploration ones.
- Grade selection: laboratory practice avoids high and low grades.

The study shows that the major cause of the observed differences is the grade selection, but also that the number of laboratory tests is certainly too small with regards to the spatial variability of the grades. The consequence is that the sampling protocol for the metallurgical recovery tests shall be reconsidered if one wants to use them jointly with exploratory data.

For more details on this paper, follow this link:
http://www.geomin.cl/evento2011/index.php?lang=en

INTRODUCTION

Mine planning requests the estimation of head grade at the scale of production blocks but in fact the economical variable is the grade recovered after a complex geo-metallurgical process (here flotation). To estimate the head (also called "total") grades, geologists require the drilling of a large amount of holes, producing, like our concern here, about 4,000 10 m-length samples. This variable is later called CuT_drill.

To estimate the recovered grade CuR, lab operators resample the drill holes, mixing them on different supports and then simulate the flotation process in laboratory at small scale, producing hundreds pairs of measurements later called CuT_lab and CuR_lab. Then a linear regression between CuR_lab and CuT_lab is built to obtain regression coefficients applied to the previous estimations of CuT_drill at each production block.

The recovery calculated by this way is too optimistic, due to the lab process and the size of the support, as one can see on Figure 1-a where the correlation between CuT_lab and CuR_lab is almost perfect, giving a recovery equal to 0.97. This is the reason why another factor is used, called "scale factor" (being in fact a "safety factor") which drastically reduces the resulting recovery to about 0.8.

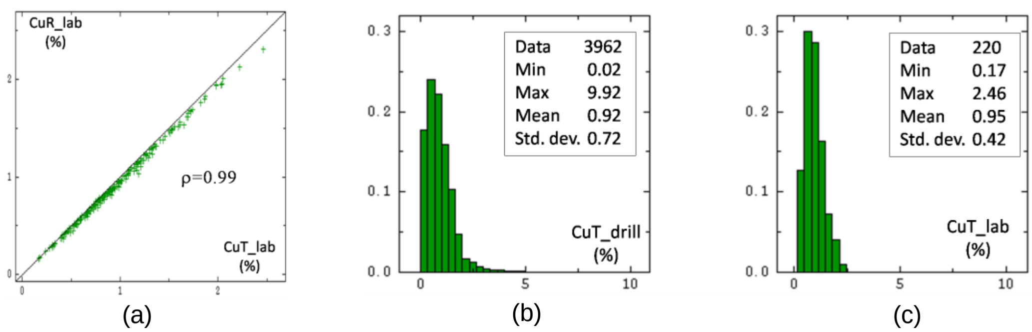

Figure 1 (a) Scatter diagram between CuT_lab and CuR_lab; (b) CuT_drill histogram; (c) CuT_lab histogram

Looking at the scatter diagram of Figure 1, the idea is immediately to estimate CuR, at the scale of the production block, using CuT_lab, CuR_lab together with CuT_drill data because the latter are numerous, but during the modelling, we encountered important differences between CuT_lab and CuT_drill, in terms of spatial variability.

- The distributions of CuT_drill and CuT_lab differ (Figures 1-b and 1-c). The range of CuT_drill is larger (maximum 9.92 %) where CuT_lab never exceeds 2.46 %. It is the same for low grades.
- Their variograms $\gamma(h)$ have different sills. For the curve related to CuT_lab, the short range behaviour has not been accessed by the sample spacing so the comparison with the curve related to the drill holes is submitted to interpretation (Figure 2).

This phenomenon, called "sampling effect", is the object of this paper.

We refer the reader to Chilès and Delfiner [1], for example, for the geostatistical concepts used in this paper. Applications have been done using the Isatis software.

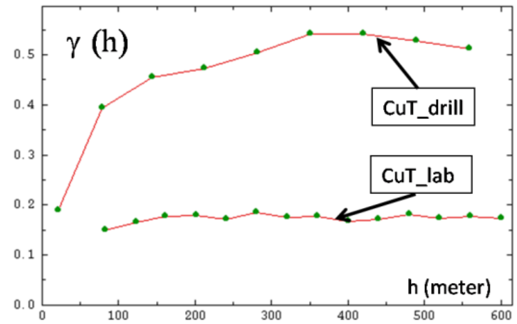

Figure 2 Drill hole and laboratory total grade variograms

LISTING THE CAUSES

The differences between CuT_drill and CuT_lab are due to several factors.

- The spatial domain covered by CuT_drill is larger than the one covered by CuT_lab.
- Drill and lab both use drill hole cores, but drill data are regularized over 10 m while lab lengths vary from 15 m to 40 m with a majority of 15 m.
- Sampling density is larger for CuT_drill than for CuT_lab (1 CuT_lab for about 20 CuT_drill).
- The range of CuT values covered by the drill-holes is larger, lab procedures avoid extreme values.

The variograms may lack robustness due to the presence of high grade values. This point could be examined with the computation of robust variogram estimates (Emery and Ortiz [2]), with variogram parameters fitted by maximum likelihood (Kinatidis and Lane [3]), or with a Gaussian transform of the data. Each of these approaches comes with its own advantages and limitations, and we remain here in the framework of the usual practice of variography.

In the following, we try to evaluate the importance of these causes in an application to the rich unit of a Chilean mine. About 4,000 samples informed in CuT_drill are available and 220 lab tests are informed with CuT_lab and CuR_lab. Variograms present some anisotropy and/or a possible West-East drift for large distances but we present their unidirectional version for clarity.

SPATIAL RESTRICTION

Figure 3 shows the CuT_drill and CuT_lab data locations in XoY projection.

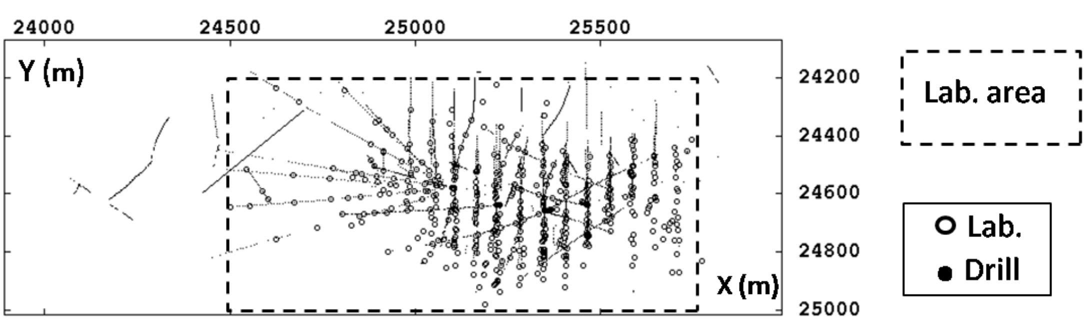

Figure 3 Base map of drill and lab measurements.

Histogram and variogram calculations of CuT_drill are restricted to the parallelepiped which surrounds the lab tests, a volume later called "lab test area" (Fig. 4). The resulting variogram of CuT_drill, in comparison with the variogram of all the drill hole data, presents a reduction of variance equal to 20 % of the sill. This indicates that the grades are not stationary. The difference between the complete and restricted data is mainly composed by an isolated group of drill holes located at the south top of the deposit (Figure 3). These isolated measurements may not belong to the same geological unit as the others, this is perhaps the reason why the lab operators did not sample them, and this could explain the difference of variability. The spatial restriction, however, only partly explains the sampling effect.

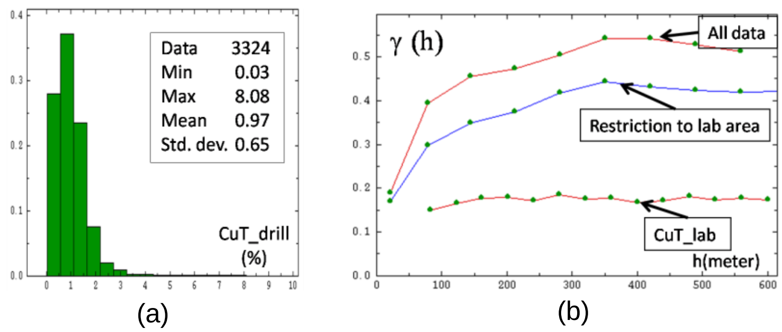

Figure 4 (a) CuT_drill distribution in lab area; (b) Impact of the spatial restriction on CuT_drill variogram

Remark: restricting the area implies reducing the number of samples by around 600 samples and also reducing the range of values (histogram of Figure 4). This could explain a part of the previous variability reduction. We consider these effects separately in the following.

REGULARISATION

From now on, analyses are restricted to the spatial domain covered by CuT_lab and the associated variogram of Figure 4 becomes the reference.

Most of lab cores are 15 m long while drill holes are essentially 10 m long.

If we focus on the first 200 m, the drill hole variogram at distance h is composed of a nugget effect C_0 and an exponential structure (sill C_1).

$$C_0 + C_1(1-e^{-\frac{h}{a}}) \quad \text{for } h \neq 0,\ C_0=0.1,\ C_1=0.285 \text{ and } a=66 \tag{1}$$

The effect of the regularisation on the nugget variance reduces it proportionally to the support. From 10 m to 15 m, the support is multiplied by 1.5 so the associated variance is divided by 1.5 and becomes 0.07.

Concerning the exponential part of Equation (1), we recall that the variogram of a variable regularized on a support v is, for distance h large in comparison with the dimension of the support

$$\gamma_v(h) = \gamma(h) - \bar{\gamma}(v,v) \tag{2}$$

where $\bar{\gamma}(v,v)$ is given by

$$\bar{\gamma}(v,v) = \frac{1}{v^2}\int_v\int_v \gamma(x-y)dxdy \tag{3}$$

In our case, both lab and exploration regularizations are supposed to be along the drill holes and the diameter of the core (some inches) is small compared to the length involved (more than 10 meters) so finally, we have 1D integrals in formula (3). This gives, for the exponential structure

$$\bar{\gamma}(l,l) = 1 - \frac{a^2}{l^2}[2e^{-\frac{l}{a}} + \frac{2l}{a} - 2] \simeq \frac{l}{3a} \tag{4}$$

For l=15 m (resp. 10 m) we obtain 0.075 (resp. 0.0505).

In percentage of the sill C of the underlying point support variogram, the reduction of variance between the lab and the exploration data is equal to the difference of these quantities and we obtain 2.5 %.

Now we calculate C. For distance h greater than the practical range, formula (2) becomes

$$C_1 \simeq C(1-\bar{\gamma}(10,10)) \tag{5}$$

and we obtain finally

$$C = \frac{0.285}{1-0.0505} = 0.3 \tag{6}$$

2.5 % of this quantity gives about 0.01 to add to the previous 0.03 associated with the nugget effect. Figure 5 shows the relative importance of these quantities.

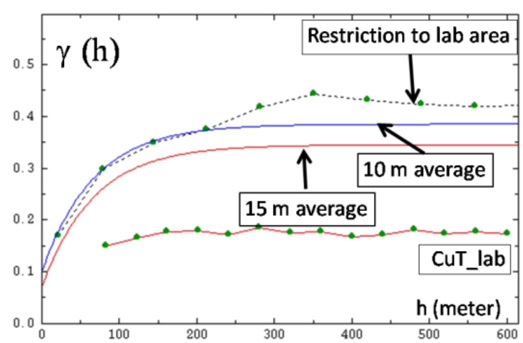

Figure 5 Impact of the regularization on CuT_drill variogram

We focused here on the main structures - we omit the longer range one, - but one can easily see that the order of magnitude of the variance reduction due to the regularization is small compared to the other sampling effects investigated in this paper.

SAMPLING DENSITY

The area contains 3,324 drill hole samples and 220 lab tests. The idea is to reduce the sampling density of CuT_drill up to the lab sampling density, while keeping a complete covering of the domain. For this, using stratified random sampling, we first divide the initial set in approximately two subsets (each one sampling the whole domain) and for each one we calculate the variogram. Then each subset is again divided in two, and so on, until arriving to small sets of about 200 measurements, thus comparable to the lab dataset.

Figure 6 shows the results. We present the variograms of the 2, 4, 8, 16 subsets having respectively 1,660, 830, 415, 207 samples. CuT_lab variogram is kept for comparison.

When the sampling density decreases, one observes an increase of the uncertainty on the variogram. With 3,300 or 1,660 or 830 samples, the sampling is still representative and the variograms do not change a lot; they all have the same behaviour. When we reduce the samples to about 400 or 200 samples, we obtain a set of variograms which have approximately the same shape, but with sills varying from half to twice the reference one.

Most of the curves differ by a vertical shift. When we model one of them in order to perform a kriging (Chilès and Delfiner [1]), we just change the percentage of nugget effect in the model and this directly affects the kriging weights and the estimation, the consequence of this uncertainty is very important. We can state that 220 CuT_drill is not enough to do a good mapping of the head grades; we would need at least 800 to get a variogram with relatively small uncertainty using the usual variogram estimate. If the objective of CuT_lab set is to be representative of CuT_drill, 220 CuT_lab is not enough neither.

What about the variance reduction? Does sampling density explain what we observe? We cannot answer this question. With only 220 CuT_lab, but with different locations (and still covering the domain), we obtain a curve which can be at the level of 0.4 or even higher. Perhaps the fact that the curves are never below 0.2 (the level of CuT_lab) indicates that the sampling density does not explain all the reduction, but this is not sure because, in relation to the important variability, if we imagine choosing 220 samples covering the domain with grades belonging to a tiny interval, one would obtain an almost null variogram.

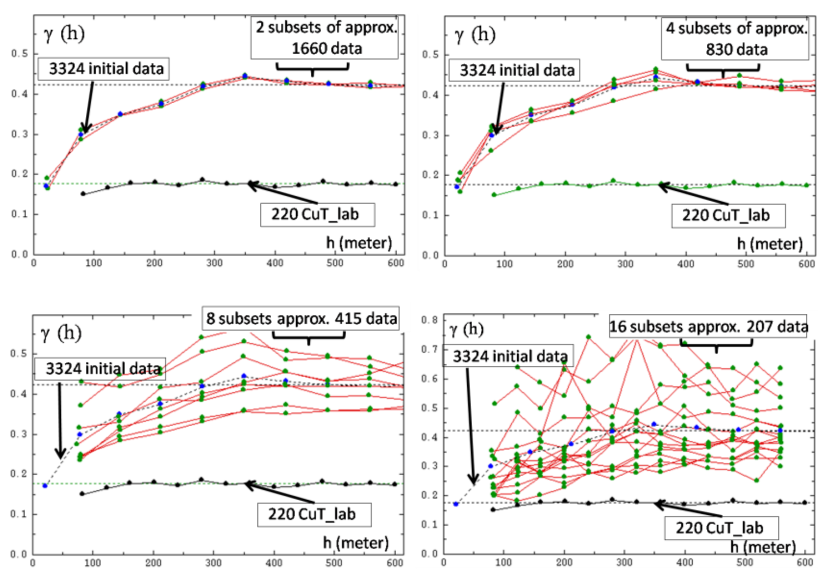

Figure 6 Impact of the sampling density on CuT_drill variogram. Data belong to lab area.

GRADE SELECTION

Histogram of CuT_lab (Figure 1-c) shows that the grades never exceed 2.45 % because:

- Lab operator mixes samples along drill holes on a length ranging from 10 to 40 m and this tends to reduce the extreme values.
- Lab operator avoids high grades (and low ones) because they are not representative of the 10 m x 15 m x 15 m production blocks.

We previously quantified the impact of the regularization and we now mimic the preferential sampling by omitting, among the 3,324 CuT_drill at our disposal, the 90 values that are greater than 2.45 %. Figure 7 shows the variogram of the remaining 3,234 data and of the 16 subsets of approximately 200 data.

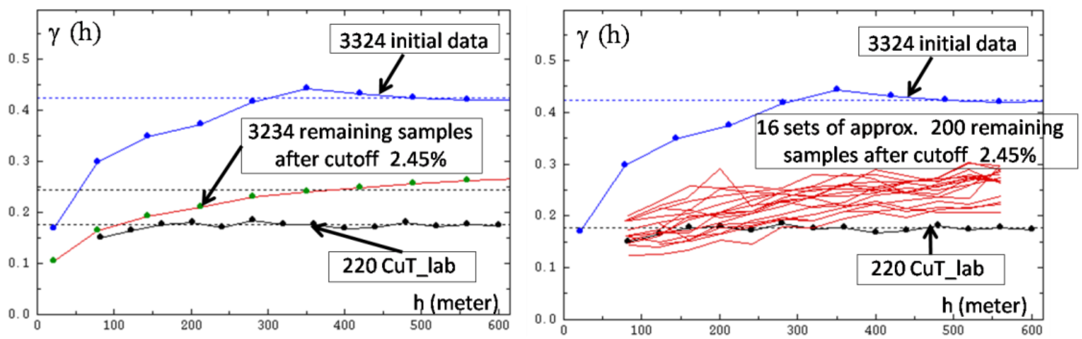

Figure 7 Cut-off 2.45%. Left (resp right) 3,234 (resp 16 sets of 200) CuT_drill values are used.

With the cut-off applied on the initial set, the sill decrease from 0.42 to 0.24. Less than 3 % of the values explain 40 % of the variance reduction; one finds here the major cause of the phenomenon. Applying the cut-off on the small subsets of 200 values, one observes that the uncertainty on the variogram decreases.

CONCLUSIONS

Tests of the so called "sampling effect" lead to sort the importance of the causes (Figure 8).

- The spatial restriction and the grade selection essentially affect the sills of the variograms and keep the behaviour. So in case of kriging with those different sills, the result will not change, only the kriging variance will.
- The combination of the spatial restriction and the grade selection explains three quarter of the variance reduction.
- The effect of the regularization is small.

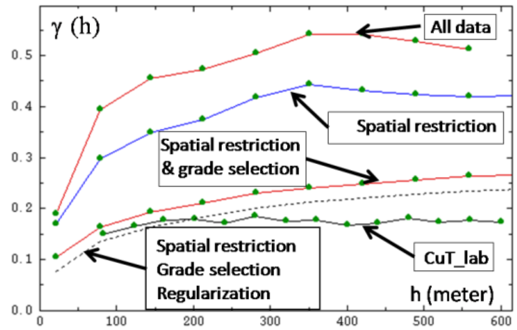

Figure 8 Summary of the different causes of the sampling effect

Concerning the sampling density, in bottom right of Figure 6, all the curves are equivalent because

- They cover the same spatial domain.
- For all subsets, the distributions of the distances between the samples are similar.
- Variograms are calculated with 200 points, which is used in lab procedures.

So with regards to this uncertainty, the number of lab tests is certainly not enough. It should be multiplied at least by four to become representative and used together with CuT_drill.

Now the question is: Does this practice serve the laboratory purpose which consists of plotting a regression line to infer a global recovery ratio R applied to each production block (including a scale factor)? The variograms of Figure 2 show that the long range structure seen for drill samples disappears for lab samples, so that each lab sample finally becomes an experiment statistically independent from one another at distances greater than 200 m. This reduces the dependency of the measurement from the location where it has been taken in the deposit. This leads to two remarks:

- Reducing the range of the grades reduces the domain of validity of the regression and it is questionable to apply it to estimated production blocks that can reach, in this deposit, more than 5 %, a grade greater than the cut-off used by the lab operators. The situation is similar for the low grades which are important also because they condition the pit design.
- This approach supposes that R does not depend on the location in the deposit and one knows that this is not true. The mineralogy for example is an important factor which explains the spatial variability of the recovery.

So finally, the best approach for recovery estimation is to reconsider lab practices, measure the recovery on samples that represent the range of point support values, estimate the grade recovered at the sample support scale, using exploratory and lab data together, and then consider the problem of the scale factor by itself.

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